Capturing and Categorizing Mental Models of Food Webs using QCM

Morteza Dehghani[1], Sara Unsworth[2], Andrew Lovett[1], Kenneth D. Forbus[1]

{morteza, s-unsworth, andrew-lovett, forbus}@northwestern.edu
[1]Qualitative Reasoning Group, Northwestern University
[2]Doug Medin's Research Group, Northwestern University

Abstract

This paper examines the use of qualitative representations in modeling the similarities and differences in causal reasoning for biological kinds between X[1] culture and US majority culture. Qualitative Concept Maps are used for modeling and analyzing transcripts of interviews conducted with these groups. The individual models are used to construct generalizations for the groups, which are tested both by inspection and by creating a classifier to distinguish models from these two cultures.

Introduction

Qualitative modeling could become an important tool for cognitive science, by providing formal languages for expressing human mental models. Formalization provides two benefits: First, we should be able to make predictions about what someone believes, based on what we have been able to glean of their models. Second, we should be able to use machine learning techniques to construct generalizations across particular people over time, or across people from particular groups, to concisely capture common properties of the models of people and groups. In this paper, we examine the relationship between culture, expertise, and causal reasoning in the domain of biology. Culture is defined here as the causally distributed patterns of mental representations, their public expressions, and the resultant behaviors in given ecological contexts (Atran, Medin & Ross, 2005; Sperber, 1985; 1996). People's mental representations interact to the extent that those representations can be physically transmitted in a public medium (language, dance, signs, artifacts, etc.). These public representations, in turn, are sequenced and channeled by ecological features of the environment (including the social environment) that constrain interactions between individuals.

The cultural communities involved in the present work include rural X, rural European Americans and Northwestern undergraduate students. The X live on many acres of heavily forested land in North America. The European Americans involved in this research live in the neighboring town of Y[2]. X individuals are more likely to engage in culture-specific ceremonial practices outdoors and are also more likely to simply engage in 'observing' practices (e.g., walks in the forest), whereas rural European Americans are more likely to engage in outdoor sporting activities (e.g., fishing competitions) and outdoor work-related activities (e.g., landscaping; Bang, 2007). One of our goals is to examine the similarities and differences in causal reasoning for biological kinds between these two cultures. By automatically constructing generalizations from field data, we should get a more objective perspective on these differences. One important way to test this hypothesis is to train classifiers, to automatically recognize which culture a causal model belongs to.

First, we discuss the role that culture plays in causal reasoning. Next, we describe our Qualitative Concept Map (QCM) system, used here to construct models of food webs from interview transcripts. We then describe how we use cognitive simulations of analogical matching and generalization to automatically construct generalizations that are used for classification. Experimental results are discussed, followed by related and future work.

The Role of Culture and Expertise in Reasoning about Biological Kinds

There are many reasons to believe that there might be similarities in individuals' causal understanding of relationships in nature. Medin, Atran, and their colleagues (see Atran et al., 2005; Medin & Atran, 2004), building on decades of important work in ethnobiology (see Berlin, 1992 for one summary), have found that, in spite of highly varying input, a few key principles guide the recognition and organization of biological information in extraordinarily similar ways. For instance, there is marked cross-cultural agreement on the hierarchical classification of living things, such that plants and animals are grouped according to a ranked taxonomy with mutually exclusive groupings of entities at each level (Atran, 1990; Berlin, Breedlove, & Raven, 1973; 1974; Brown, 1984; Hays, 1983; Hunn, 1977). The highest level of taxonomic organization includes the most general categories, such as

[1] Group name redacted for privacy reasons

[2] Town name redacted for privacy reasons

the folk kingdom rank (which includes groupings such as plants and animals), and lower levels distinguish between increasingly greater degrees of specificity (e.g., life forms such as tree or bird; generic species level such as oak or blue jay). The generic species level appears to be consistently privileged for inductive inference when generalizing properties across plants and animals, as it is the lowest level for which inductive power is the greatest, and only minimal inductive advantage is gained at more subordinate levels (Coley, Medin, and Atran, 1997). There is cross-cultural agreement that the appearance and behavior of every species is caused by an internal biological (and usually unspecified) essence that is inherited from the birth parents and is responsible for identity persistence in the face of physical and developmental transformation (Atran, 1998; Atran, Estin, Coley, & Medin, 1997; Gelman, 2003; Gelman & Wellman, 1991; Medin & Atran, 2004; Sousa, Atran, & Medin, 2002).

However, there is also evidence suggesting considerable variability within these universal constraints in folk biological concept formation as a function of both experience with the natural world and cultural salience (two highly related factors). For instance, Rosch and Mervis (1975) have found that the life form level is the level for which urban undergraduates possess the greatest knowledge (i.e., basic level), but Berlin (1992) found that among traditional societies in which individuals have more direct experience with the natural environment, the basic level corresponds to the generic-species level, and these differences have been attributed to differences in expertise (Medin & Atran, 2004). Other findings implicate cultural differences above and beyond expertise. For instance, some native American groups are more likely than rural European Americans to see themselves as a part of nature rather than apart from nature and to say that every creature has a role to play on Mother Earth (Bang, Unsworth, Townsend, & Medin, 2005).

When asked to sort biological kinds into categories, individuals from different communities vary not only in their taxonomic sorting but also in the degree to which they spontaneously sort along ecological dimensions, and this difference is not as predictable on the basis of expertise or experience alone. Specifically, Medin, Ross, Atran, Burnett, and Blok (2002) found that Menominee fisherman and European American fishermen, who both have similar levels of expertise about fish and fish habitats, exhibit differences in ecological sorting of fish during a regular sorting task. Menominee fishermen are significantly more likely to sort in terms of ecological relationships. This pattern was found for both expert fishermen and for nonexperts in the two communities. Furthermore, in a subsequent task involving questions about fish-fish interactions, Menominee fishermen were significantly more likely to report positive and reciprocal relations, although both groups were equally likely to report negative relations.

Similar differences in ecological reasoning were found for children from these communities, such that X children were more likely to reason about shared properties between living things on the basis of ecological relations, relative to rural European American children (Ross, Medin, Coley, & Atran, 2003). Differences in ecological reasoning appear to be the result of both culture and expertise, as rural European American children were more likely to engage in ecological-based reasoning than were urban European American children who had comparatively less experience with the natural world.

Do you think that the disappearance in the bears would affect other plants and animals in the forest?
-Probably just like shrubs and stuff that these animals the basic food sources like berry plants and stuff. And then maybe larger trees, too, because bears climb trees.
…
Because of there's a more competing for water in the soils. There's more shade, because I'm assuming it's a taller tree. So there's more shade so the ground growth couldn't grow as well. It would provide more nesting areas for the animals that use it for nesting. So they might benefit from it but they'd have less food.
-Right. And so do you think that other trees would be affected?
-Yes, because there's a competing for space. So the underbrush and that wouldn't grow as well, or any tree that's smaller.
-Yeah. And what about larger animals like bears? Do you think that they would be affected?
- If their food source was decreased because of the lack of undergrowth.

Figure 1: Excerpts from a transcript

Although prior research suggests that there are cross-cultural differences in causal models, little research has focused on directly assessing such differences. Consequently, we interviewed experts (i.e., hunters and fishermen) and novices (individuals who do not hunt or fish) from X and from European American cultural communities. Participants were presented a scenario in nature and were asked open-ended questions about the scenarios. Transcriptions of three scenarios were modeled in the present study. In each scenario, participants were told about a perturbation in an ecological system and were asked to speculate about the effects of such an event on other plants and animals in the forest. In one scenario, the perturbation involved the disappearance of all of the bears in a nearby forest. In another scenario, the perturbation involved a doubling of the bear population in a nearby forest. In a third scenario, the perturbation involved the disappearance of all of the poplar trees in a nearby forest. Each participant was presented with all three scenarios, and after each scenario participants were first allowed to openly discuss any consequences that came to mind before being probed with an exemplar (e.g., eagle) that represented a particular trophic type with respect to the perturbation species (e.g., competitor). Given the open-ended nature of the interviews, the number of probes presented to participants varied across individuals depending on the depth of initial responses and the degree to which they responded to subsequent probes.

The verbal explanations of the subjects were transcribed (see Figure 1 for example), and used as data to construct formal qualitative models expressing their beliefs. Based on previous research cited above, we predicted that X' causal mental models of nature would be more inclusive and would include more interconnections, relative to rural European Americans.

Qualitative Concept Maps

We use the Qualitative Concept Maps (QCM) system to create formal models based on transcripts of the interviews. QCM provides a friendly interface for

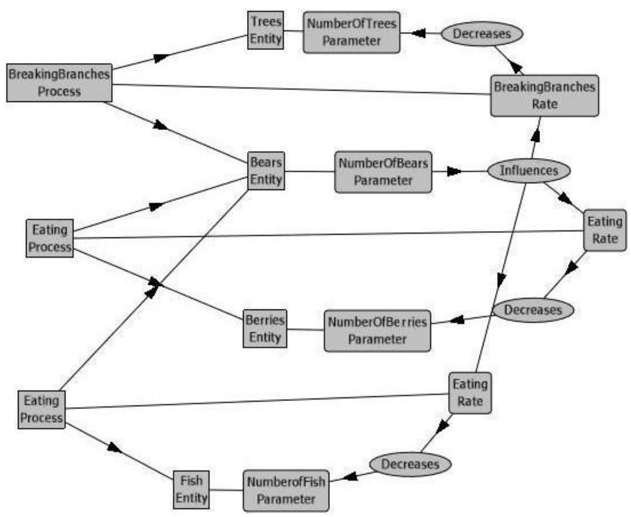

Figure 2: A QCM model

experimenters to explore causal models using Qualitative Process (QP) Theory semantics (Forbus, 1984). QP theory as a representation language for physical phenomena includes:

- Continuous parameters (*quantities*)
- Causal relationships between them (*influences*)
- Mechanisms underlying physical causality (*physical processes*)

QCM uses a concept map interface (Novak & Gowin, 1984). QCM automatically checks for any modeling errors which violate the laws of QP theory, providing detailed error messages.

QCM uses multiple panes to represent distinct qualitative states. This is important for capturing changes over time. For example, in the scenarios outlined above, participants would often discuss immediate effects of a change followed by long-term effects of changes. Figure 2 illustrates one pane from a model for the Bears Disappearing scenario. The *meta-pane* (Figure 3) allows modelers to see all the states at once. Modelers can easily extend the vocabulary of specific processes and quantities used in the models, to expedite model creation.

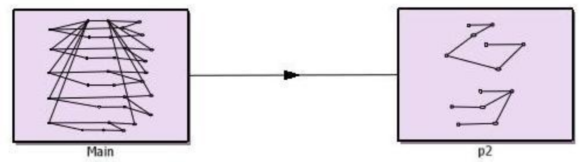

Figure 3: The meta-pane provides an overview of the qualitative states in the model

QCM can import and export models via GraphML (Brandes et al., 2002), allowing graphs drawn in QCM to be easily viewed in other graph drawing programs. This facilitates collaboration between modelers. More importantly, for cognitive simulation purposes, models can be exported as predicate calculus statements. This enables QCM models to be used in a variety of reasoning systems. We are also working on directly importing propositional statements into QCM, to visualize models constructed via other systems. In this paper, we use the propositional statements produced by QCM to automatically construct generalizations, testing them via learning a classifier.

Computational Experiments

Here we describe a method for building generalizations from transcripts modeled in QCM. These generalizations make explicit the common structure found in the models. They can also be used to automatically categorize subsequent models, based on the culture they belong to. The learning technique that we use in this experiment has previously been used in automatic sketch recognition (Lovett, Dehghani and Forbus 2007), automatic music genre classification (Dehghani and Lovett 2006) and classifying terrorist activities by perpetrator (Halstead and Forbus 2007**)**. The major benefit of this technique is that, although it only requires very small training sets, utilizing qualitative representations it can achieve the performance of machine learning algorithms which require orders of magnitude larger data sets.

Comparison and Generalization

We compare representations using the Structure-Mapping Engine (SME) (Falkenhainer, Forbus and Gentner, 1989). SME is a computational model of similarity and analogy based on Gentner's (1983) structure mapping theory of analogy in humans. It works on structured representations, consisting of entities, attributes of entities and relations. There are both first-order relations between entities and higher-order relations between other relations. Given two representations in this form, a *base case* and a *target case*, SME aligns their common structure to form a mapping between the cases. This mapping consists of a set of correspondences between entities and expressions in the two cases. SME tries to find mappings that maximize *systematicity*; that is, it prefers mappings with higher-order relations and relationally connected structure.

Our system learns categories of objects using SEQL (Kuehne et al, 2000), a model of generalization built on SME. SEQL is based on the idea that when humans are exposed to multiple exemplars of a category, they construct generalizations by comparing the exemplars and abstracting out the common structure. SEQL does this by comparing individual cases with SME. For each category, SEQL maintains a list of generalizations and exemplars. Each new incoming exemplar is compared against the existing generalizations, and if it is sufficiently similar, the generalization is refined based on their common structure. Otherwise, the exemplar is compared against other, unassimilated exemplars. If sufficiently close to one of them, a new generalization is formed from their common structure. Originally non-overlapping structure was simply thrown away. Now, SEQL associates a probability with every expression in a generalization which is updated with each new exemplar, and only gets rid of very low-probability structure (Halstead and Forbus 2005). SEQL can be forced to construct a single generalization for a category by simply setting the assimilation threshold to be extremely low.

Results

81 transcripts, generated in response to three food web scenarios, were modeled using QCM. The transcripts for two additional scenarios were excluded because participants rarely responded to these scenarios in detail. These two scenarios were structurally similar to the other scenarios presented and were always presented at the end of the interview, and so it is speculated that participants perceived repetition as they progressed through the interview and reduced responding as a result.

We randomly divided the models into a test and a training set 1,000 different times. In each run, we used SEQL to produce two generalizations, one for X and one for non-X, from the models in the training set. These generalizations were then used to classify models in the test set by using SME to compare each model with the two generalizations. We calculated the percentage of the model's expressions that aligned with each generalization, and the percentage of the generalization's expressions that aligned with the model, and classified test models based on which generalization it had more in common with. We tabulated successful classification by cultural group and averaged the results over all 1,000 trials.

Table 1 shows the results of our experiment. In the first two columns the percentage of X models being correctly classified as X and non-X being classified as non-X are shown. The last column shows the overall accuracy of the system. The average accuracy across the three scenarios was 64%.

Our system was able to automatically compute generalizations which differentiated between the two

	X	Non-X	Overall Accuracy
Bears Disappearing	65%	57%	61%
Bears Doubling	82%	52%	67%
Poplar Disappearing	64%	64%	64%

Table 1: Performance of the classification system

culture models. Our system was also able to find similarities in causal models from the same culture. By examining the system's results, we can gain insights into the differences and similarities between the models. Specifically, we found that the number of facts that were consistent across individuals was higher in X models. We examined the generalizations from a single test run for each scenario, in which the system achieved 70% accuracy. For this test run, there were 24 facts found consistently across all X models vs. 16 facts for non- X. Also, the number of consistent causal relations was higher among X. X models contained 4 causal relations found consistently across all models, whereas non-X models only contained 2. We can conclude from this result that causal understanding of relationships in nature is more homogeneous among X than among non- X.

As per our prediction, the generalizations that were made from X models were more detailed, larger and therefore subsumed other smaller generalizations. This had the unfortunate side-effect of biasing models towards being classified as X. However, as mentioned above, the open-ended nature of the interviews led to variation in the number of probes presented to participants across individuals, and the resultant variability in responses can introduce some difficulty when attempting to evaluate similarities in causal maps. Open-ended interviews are useful for exploratory investigations of the ways in which participants are likely to respond to hypothetical scenarios, and future research can build on the knowledge gained here. Specifically, the present results can now be used as a basis for designing a more structured survey in which participants are presented with a larger, more comprehensive list of animals and plants that represent all of the trophic levels and ecological considerations mentioned by X and non-X adults of varying hunting and fishing expertise. This should help provide the most systematic probing of their knowledge.

Related Work

QCM can be thought of as the second generation VModel (Forbus, Carney, Harris and Sherin, 2001). VModel was developed to help middle-school students learn science. Like QCM, it uses a subset of QP theory to provide strong semantics. However, VModel was limited to single-state reasoning, whereas QCM can be used to model physical causal phenomena with multiple states. Similar differences hold with Betty's Brain (Biswas *et al* 2001), which provides a concept-map interface for single-state qualitative reasoning designed for middle-school students.

The closest other qualitative modeling tools are MOBUM (Machado & Bredeweg, 2001) and VISIGARP (Bouwer & Bredeweg 2001), which have lead to Garp3.[3] Like QCM, these environments are aimed at researchers, but their focus is on constructing models for qualitative simulation, using generic, first-principles domain theories. QCM focuses instead on helping capture concrete, situation-specific qualitative explanations of phenomena. Thus it provides a useful tool for scientists working with interview data.

Discussion

We have shown that cultural differences in causal reasoning about food webs can be captured to some degree in terms of similarities and differences in qualitative models extracted from transcript data. Although previous manual analysis of the transcripts have shown to be very difficult and time consuming, by using SEQL and SME we were able to find similarities and differences and automatically cluster causal models built from the transcripts. While the results are significant, the accuracy could be improved, and we plan to use a more stringent interview protocol to test this. We also plan to use more than one expert for modeling the results. Also, we are investigating how causal models of hunters (experts) are different from non-hunters (novices).

More generally, we are encouraged by the success of QCM in providing a scientist friendly environment, where QP theory can be used to model interview data. We plan to extend QCM in several ways. First, we plan to use similarity-based qualitative simulation (Yan & Forbus, 2005) to support creating predictions based on learned generalizations from transcript models. Second, we plan to integrate our qualitative simulator (Gizmo), to provide a complementary first-principles simulation engine. Finally, we plan to provide a more comprehensive interface, to provide a unified platform for representing, clustering, and reasoning about qualitative models derived from data.

Acknowledgments

This research was supported in part by a grant from the US Air Force Office of Scientific Research. We thank Doug Medin for many useful insights.

[3] http://hcs.science.uva.nl/QRM/index.html

References

Atran, S. (1990). *Cognitive Foundations of Natural History*. Cambridge, England: Cambridge University Press.

Atran, S. (1998). Folk biology and the anthropology of science: Cognitive universals and cultural particulars. *Behavioral and Brain Sciences, 21*(4), 547-609.

Atran, S., Estin, P., Coley, J., & Medin, D. L. (1997). Generic species and basic levels: Essence and appearance in folkbiology. *Journal of Ethnobiology, 17*, 22-45.

Atran, S., Medin, D. L., Ross, N., Lynch, E. B. Vapnarsky, V., Ucan Ek', E., et al. (2002). Folkecology, cultural epidemiology, and the spirit of the commons: A garden experiment in the Maya Lowlands, 1991-2001. *Current Anthropology, 43*, 421-450.

Atran, S., Medin, D. L., and Ross, N. O. (2005). The cultural mind: Environmental decision making and cultural modeling within and across populations. *Psychological Review, 112*, 744-776.

Bang, M., and Medin, D. L. (in preparation). The cultural context of learning: Native-American science education.

Bang, M., Townsend, J., Unsworth, S. J., and Medin, D. L. (2005). *Cultural models of nature and their relevance to science education.* Paper presented at the 2005 Annual Meeting of the American Education Research Association, Montreal, Quebec.

Berlin, B. (1992). *Ethnobiological Classification*. Princeton, NJ: Princeton University Press.

Berlin, B., Breedlove, D. E., and Raven, P. H. (1973). General Principles of Classification and Nomenclature in Folk Biology. *American Anthropologist, 75*, 214-242.

Berlin, B., Breedlove, D. E., and Raven, P. H. (1974). *Principles of Tzeltal plant classification; an introduction to the botanical ethnography of a Mayan-speaking people of highland Chiapas*. New York: Academic Press.

Biswas, G., Schwartz, D., Bransford, J. & The Teachable Agents Group at Vanderbilt. Technology Support for Complex Problem Solving: From SAD Environments to AI. In Forbus, K. and Feltovich, P. (eds) 2001 *Smart Machines in Education: The coming revolution in educational technology*. AAAI Press.

Brandes U., Eiglsperger M., Herman I., Himsolt M., and Marshall M. S. (2001): GraphML Progress Report: Structural Layer Proposal. Proc. 9th International Symposium. Graph Drawing (GD '01), LNCS 2265, pp. 501-512.

Brown, C. (1984). *Language and Living Things: Uniformities in Folk Classification and Naming*. New Brunswick, NJ: Rutgers University Press.

Bouwer A. and Bredeweg B. (2001): VISIGARP: graphical representation of qualitative simulation models, in: *Artificial Intelligence in Education – AI-ED in the Wired and Wireless Future*, J.D. Moore, G. Luckhardt Redfield and J.L. Johnson, eds, IOS Press/Ohmsha, Osaka, Japan, 2001, pp. 294–305.

Coley, J., Medin, D. L., and Atran, S. (1997). Does rank have its privilege? Inductive inferences in folkbiological taxonomies. *Cognition, 63*(73-112).

Dehghani, M., and Lovett, A. (2006). Efficient Genre Classification using Qualitative Representations. In the Proceedings of the 7th International Conference on Music Information Retrieval (ISMIR'06). Victoria Canada.

Falkenhainer, B., Forbus, K., and Gentner, D. 1989. The Structure-Mapping Engine: Algorithms and Examples. Artificial Intelligence 41: 1-63

Forbus, K. (1984). Qualitative process theory. Artificial Intelligence,24, 85-168.

Forbus, K., Carney, K., Harris, R., and Sherin, B. (2001) Modeling Environment for Middle-School Students: a Progress Report. In G. Biswas ed. *Papers from the 2001 Qualitative Reasoning Workshop* Stoughton, WI, The Printing House.

Gelman, S. A. (2003). *The essential child : origins of essentialism in everyday thought*. New York: Oxford University Press.

Gentner, D. (1983). Structure-Mapping: A Theoretical Framework for Analogy. Cognitive Science 7: 155-170.

Gelman, R., and Wellman, H. M. (1991). Insides and essences. *Cognition, 38*, 214-244.

Halstead, D. and Forbus, K. (2007). Some Effects of a Reduced Relational Vocabulary on the Whodunit Problem. In *Proceedings of the International Joint Conference on Artificial Intelligence.*

Halstead, D., and Forbus, K. (2005). Transforming between Propositions and Features: Bridging the Gap. In Proceedings of the 20th National Conference on Artificial Intelligence (AAAI'05). Pittsburgh, PA: AAAI Press.

Hays, T. (1983). Ndumba folkbiology and general principles of ethnobotanical classification and nomenclature. *American Anthropologist, 85*, 592-611.

Hunn, E. (1977). *Tzeltal Folk Zoology: The Classification of Discontinuities in Nature*. New York: Academic Press.

Kuehne, S., Forbus, K., Gentner, D. and Quinn, B. (2000). SEQL: Category Learning as Progressive Abstraction Using Structure Mapping. In Proceedings of the 22nd Annual Conference of the Cognitive Science Society, 770-775. Philadelphia, PA.

Lopez, A., Atran, S., Coley, J. D., & Medin, D. L. (1997). The tree of life: Universal and cultural features of folkbiological taxonomies and inductions. *Cognitive Psychology, 32*(3), 251-295.

Lovett, M., Dehghani, M., Forbus K. (2007). Incremental Learning of Perceptual Categories for Open-Domain Sketch Recognition. In the Proceedings of the 20th International Joint Conference on Artificial Intelligence (IJCAI'07). Hyderabad, India: AAAI Press.

Machado, V. and Bredeweg, B. 2001. Towards Interactive Tools for Constructing Articulate Simulations. *Proceedings of QR01*

Medin, D. L., and Atran, S. (2004). The Native Mind: Biological Categorization and Reasoning in Development and Across Cultures. *Psychological Review, 111*(4), 960-983.

Medin, D. L., Ross, N. O., Atran, S., Burnett, R., and Blok, S. (2002). Categorization and Reasoning in Relation to Culture and Expertise. On *Psychology of Learning and Motivation, 41*. New York: Academic Press.

J.D. Novak and D.B. Gowin, Learning How To Learn, New York: Cambridge University Press. 1984.

Proffitt, J. B., Coley, J. D., and Medin, D. L. (2000). Expertise and category-based induction. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 26*(4), 811-828.

Rosch, E., and Mervis, C. B. (1975). Family resemblances: Studies in the internal structure of categories. *Cognitive Psychology, 7*(4), 573-605.

Ross, N., Medin, D., Coley, J. D., and Atran, S. (2003). Cultural and experimental differences in the development of folkbiological induction. *Cognitive Development, 18*(1), 25-47.

Sousa, P., Atran, S., and Medin, D. (2002). Essentialism and folkbiology: Evidence from Brazil. *Journal of Cognition and Culture, 2*(3), 195-223.

Sperber, D. (1985). Anthropology and Psychology: Towards an epidemiology of representations. *Man, 20*, 73-89.

Sperber, D. (1996). *Explaining Culture: A Naturalistic Approach*. Oxford: Blackwell.

Yan, J. and Forbus, K. 2005. Similarity-based qualitative simulation. *Proceedings of the 27th Annual Meeting of the Cognitive Science Society.*